

Comparison of Techniques for Ground Target Tracking

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Chih-Chung Ke
Center for Multisource
Information Fusion
State University of New York at
Buffalo
Buffalo, NY 14226

Jesús García Herrero
GPSS-SSR-ETSIT
Universidad Politécnica de Madrid.
Ciudad Universitaria s/n, 28040
Madrid, Spain

James Llinas
Center for Multisource
Information Fusion
State University of New York at
Buffalo
Buffalo, NY 14226

ABSTRACT

There have been a lot of studies addressing target-tracking problems, in which targets like aircraft and missiles can move freely in the air without hard spatial constraints. Tracking ground targets is a completely different case. Variable terrain structures not only limit the target's moving capability, but also degrade the quality of measurement data. This paper describes an exploratory research project which studied the tracking of a single ground target via traditional and atypical approaches. Traditional Kalman techniques taking into account the additional information provided by the ground restrictions in the tracking process, a road network in our study, were implemented. Additionally, another tracker using the Hidden Markov Model (HMM) with transition array was also developed under the same scenario. The results showed that Kalman techniques with available road information significantly outperform the conventional Kalman approaches in terms of longitudinal and transversal errors at the time when the target maneuvers. The proposed adaptive HMM tracker, composed of some regional HMM trackers, is not sensitive to transversal maneuvers, but may yield large longitudinal errors at the time when the target approaches the boundary of each subscenario.

Keywords: Ground Target Tracking, Interacting Multiple Models, Hidden Markov Models, Viterbi algorithm.

1 Introduction

Tracking ground targets is much more difficult than aerial targets due to topographic variations that can influence a target's motion patterns and obscurity to observation. An exhaustive literature survey [1] showed that not much specific work has been done for this tracking problem, certainly not when compared to freely moving 3D targets. Basically, we are particularly interested in two among several categories of trackers for point ground targets that have no spatial extent. The first category includes the Kalman-based approaches where a number of studies taking advantage of available terrain information, such as elevation or roads, have been carried out. For example, in [2], a terrain aided passive estimation approach was developed as an improved solution to the problem of accurately locating ground targets from aircraft referenced passive sensors. The algorithm fused angular target measurements (azimuth and elevation angle) from all available sensors along with the stored elevation data to obtain the least squared error estimates of the target location. In [3], an Interacting Multiple Model (IMM) estimator of variable structures was designed where the filter modes associated with each target were adaptively modified, added or removed, depending on the topography for tracking on-road and off-road targets, within the same framework. Other work regarding tracking processes involving map information in Kalman approaches can also be found [4], [5].

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The second type of ground tracker is based on the theory of Hidden Markov Models (HMM) [6], [7], [8]. In this approach, it is assumed that targets moved in an area characterized as a rectangular grid at discrete time instants. The system modeled the states as the discrete target locations, and the state transitions as the target's possible geographic movement. The actual history of the target's location versus time could be retrieved using the Viterbi algorithm. However, it was not explicitly explained in these studies how to incorporate varying terrain knowledge into the transition array.

The road restriction is the most attractive terrain feature that interests us. In this paper, the scenario map, with solely the road network as the topographic feature, was taken from a small area in France where a battle between German and French forces took place in World War II. We refined the above two approaches for tracking a single ground target by presenting a generalized structure to incorporate the road information, and developed innovative tracking schemes with target dynamics guided by the road map. A multitarget scenario including the effects of data association processing was not considered for this study but will be explored in future studies. Since the elevation data was not of concern, all trackers were modeled in 2D space.

Note that we only take care of the development of tracking algorithms. It is not a hybrid method that involves a high-level strategic decision-making scheme based on the track of the target. As a matter of fact, in the same project we work on, there is another group dealing with belief revision and automatic reasoning for decision support in the same battle scenario [9].

This paper is organized as follows. In section 2, several trackers based on Kalman filtering with and without ground information are proposed and analyzed. In section 3, an adaptive HMM-based tracker is presented where the coverage of the geographic region differs as the target moves. The simulation results are illustrated and discussed in section 4. Finally, the concluding remarks are made in section 5.

2 Kalman-based Tracking Techniques

In this section, some Kalman-based approaches for tracking a ground target moving on a road network are proposed and analyzed. A representation of this network, besides the methods to deal with it, is proposed, and the effects of using this additional source of knowledge on the final performance are shown later.

Here, we focus on the estimation of location and kinematic parameters of the target. Within the Kalman filter framework, there are two possible ways to include the road information in the models: 1) the modification of data reported by sensors, according to the road restrictions, and 2) a "tuning" in the model of target dynamics. We will explore both options, especially the second that involves different ways to incorporate the road information in the dynamic model of the target such that the Kalman equations can be changed correspondingly.

It can be asserted that the main issue determining the performance of Kalman filters is the correct model of target dynamics. Although it provides highly efficient and optimal solutions for scenarios where targets move at constant velocity, biases and bad performance in the transient periods can often result when targets maneuver. The representation of maneuvers as additive Gaussian pseudonoise is a conventional way of modeling target dynamics, although maneuver acceleration is naturally discontinuous and may not be well represented. Usually, an important factor to change the dynamics is the variance of the process noise [10]. The maneuver detection and adaptation problem has been studied since Moose *et al.* [11]. It turns out that the IMM algorithm is one of the best schemes to change the dynamic model adaptively [12]. The methodology suggested here to incorporate the ground information in the tracker involves the adaptation of the dynamic model parameters, depending on the characteristics of traversed ground elements. Therefore, an algorithm is implemented to locate the target inside the road network for updating the target dynamic model. It can be particularly effective in dealing with transversal maneuvers that occur when the target follows the turn in a curved road, or changes the heading direction at the junction of roads. This type of maneuver can be predicted from the target locations in the map such that the model can be modified to take them into account. The longitudinal maneuvers such as stops or accelerations depend on the driver's intention and cannot be predicted. However, the direction and magnitude can be adjusted based on the road characteristics.

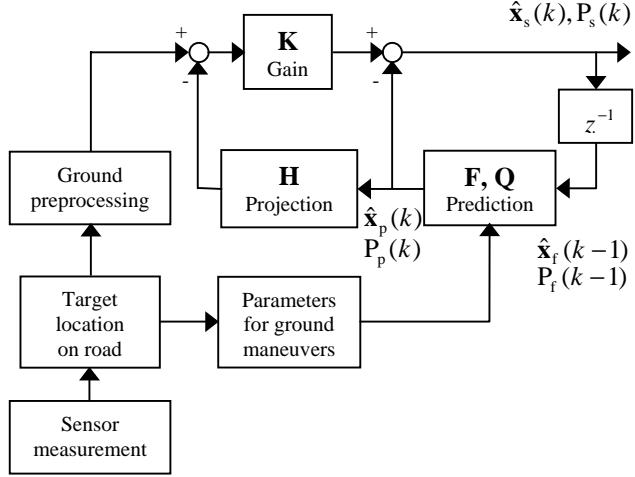


Figure 1: The proposed ground target tracking architecture.

The block diagram of the proposed system is shown in Figure 1. The basic structures and equations of the Kalman filter are augmented with the logic to locate the target on the ground and the additional processes to incorporate the ground information into the prediction and observation models. $\hat{\mathbf{x}}_s(k)$ and $\mathbf{P}_s(k)$ denote the smoothed estimation and covariance matrix, while $\hat{\mathbf{x}}_p(k)$ and $\mathbf{P}_p(k)$ are the predicted estimation and associated covariance. The prediction stage involves the transition matrix, \mathbf{F} , and the covariance of process noise, \mathbf{Q} . The updating phase is controlled by the gain matrix, \mathbf{K} , derived from the conventional Kalman equations.

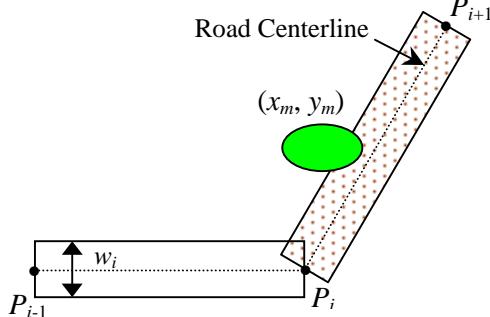


Figure 2: Geographic representation illustrating the overlap of the road segment and the uncertainty region for sensor measurement.

The basic idea to identify if the target is inside a road is depicted in Figure 2. The road structure is composed of a number of segments linking a series of waypoints P_i and the associated widths w_i . To determine if an observation falls inside a road segment, we need to search if there is an overlap between the rectangular road segment and the uncertainty region of measurement, which is a geographic ellipse expressed by the following equation

$$[x_m - x \quad y_m - y] \mathbf{R}^{-1} \begin{bmatrix} x_m - x \\ y_m - y \end{bmatrix} \leq \alpha \quad (1)$$

where (x_m, y_m) is the sensor measurement, \mathbf{R} is the associated covariance matrix, depending on the assumed sensor model, and α is the probability of locating the target inside the uncertainty region. This is a typical procedure to find out the road segment where the target is moving, considering only the sensor report. In some complex situations, such as when the target is approaching a junction where several road segments overlap, the procedure can be improved using the estimated locations from the tracker.

2.1 Map-Tuned Variance Model

The first method to incorporate the ground information into the dynamics contains a dynamic adaptation of the noise variance for maneuvers. As the target approaches the end of a road segment, there is a probable transversal maneuver for the target to keep inside the road. The value of this process variance can be “tuned”, based on the distance between the target and the next waypoint, as well as the estimation of groundspeed. The assumed dynamic model is that the target moves with a constant velocity plus additive white Gaussian acceleration process, given by

$$\begin{bmatrix} x(k+1) \\ y(k+1) \\ v_x(k+1) \\ v_y(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t_k & 0 \\ 0 & 1 & 0 & \Delta t_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{bmatrix} + a_x(k) \begin{bmatrix} \Delta t_k^2/2 \\ 0 \\ \Delta t_k \\ 0 \end{bmatrix} + a_y(k) \begin{bmatrix} 0 \\ \Delta t_k^2/2 \\ 0 \\ \Delta t_k \end{bmatrix}, \quad (2)$$

$$\mathbf{Q}(k) = \sigma_a^2 \begin{bmatrix} \Delta t_k^4/4 & 0 & \Delta t_k^4/2 & 0 \\ 0 & \Delta t_k^4/4 & 0 & \Delta t_k^4/2 \\ \Delta t_k^4/2 & 0 & \Delta t_k^2 & 0 \\ 0 & \Delta t_k^4/2 & 0 & \Delta t_k^2 \end{bmatrix}. \quad (3)$$

The parameter σ_a , the standard deviation of processes a_x and a_y , is maintained low while the target is inside a straight road segment, and is increased when it is getting close to the end of segment. The increase of variance depends on the target dynamic characteristics and the current speed. This is a robust and easy scheme to adapt transversal maneuvers. Basically, it avoids the biases due to the mismatch between the constant velocity prediction model and transversal accelerations, but increases the noise in the estimators.

2.2 Curvilinear Model

A more sophisticated method, named the “curvilinear model”, may be used as an alternative to deal with the influences of the road segment orientation on the dynamic model of target. If the target is moving inside the road at constant speed, its velocity vector should follow the orientation of the centerline. During the transition period from one segment to next, this approach models the target trajectory as a circular arc. This type of dynamic is described by the following nonlinear equations

$$\begin{bmatrix} x(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} + r \begin{bmatrix} \cos \theta_{k+1} - \cos \theta_k \\ \sin \theta_{k+1} - \sin \theta_k \end{bmatrix},$$

$$\begin{bmatrix} v_x(k+1) \\ v_y(k+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \cdot \begin{bmatrix} v_x(k) \\ v_y(k) \end{bmatrix},$$

$$r = \frac{|v|^2}{a_t}, \quad \theta_k = \tan^{-1} \left[\frac{v_y(k)}{v_x(k)} \right], \quad \theta_{k+1} = \theta_k + \frac{a_t}{|v|} \Delta t_k \quad (4)$$

where θ is the orientation and a_t is the transversal acceleration of the target. If the jump in orientation from one segment to the next is low enough, these equations can be linearized with a first order approximation and included in a linearized extended Kalman filter with model

$$\begin{bmatrix} x(k+1) \\ y(k+1) \\ v_x(k+1) \\ v_y(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t_k \cos \frac{\alpha}{2} & -\Delta t_k \sin \frac{\alpha}{2} \\ 0 & 1 & \Delta t_k \sin \frac{\alpha}{2} & \Delta t_k \cos \frac{\alpha}{2} \\ 0 & 0 & \cos \alpha & -\sin \alpha \\ 0 & 0 & \sin \alpha & \cos \alpha \end{bmatrix} \cdot \begin{bmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{bmatrix} + \frac{a_l}{2} \begin{bmatrix} \Delta t_k^2 \cos \theta \\ \Delta t_k^2 \sin \theta \\ 2 \cdot \Delta t_k \cos \theta \\ 2 \cdot \Delta t_k \sin \theta \end{bmatrix} \quad (5)$$

where α is the angle between the estimated velocity and the centerline.

Some studies [13], [14] have used this technique to include heading information in the dynamic equations. Here, the continuous correction of target velocity with segment orientation allows both adaptation to turns and a high degree of smoothing. The characteristic of the longitudinal maneuver noise allows the projection of the process noise in this direction to maintain a low transversal error.

Note that a key component in the entire tracker is the correct target location in the current traversed road segment. A robust method is required to ensure the selection of the correct road segment such that the errors in orientation and some stability problems can be reduced. Instead of selecting the nearest segment to locate the measurement in the road network, the location of the predicted estimation is determined, leading to fewer noise corrections in the changes of segments. However, a problem occurs in road branches where several segments are joined. In that case, a track splitting technique may be used to improve the results.

2.3 Map Preprocessing Technique

We continue to discuss a refined technique which preprocesses the sensor measurements with available road information by transforming the parameters of the measurement error distribution. Assume that the target location (x, y) is uniformly distributed inside the road coverage C :

$$p_C(x, y) = \begin{cases} 1/A, & (x, y) \in C \\ 0, & \text{elsewhere} \end{cases} \quad (6)$$

where A is the area of C . Then the probability density function of target location, given the sensor measurement (x_m, y_m) , can be expressed as

$$p(x, y | x_m, y_m) = \frac{l(x, y, x_m, y_m) p_C(x, y)}{\iint_C l(x, y, x_m, y_m) p_C(x, y) dx dy} \quad (7)$$

where $l(x, y, x_m, y_m)$ is the likelihood function associated with (x_m, y_m) , usually a Gaussian distribution with covariance matrix \mathbf{R} . Because the resulting likelihood function is spatially truncated and thus bounded to the road coverage, which is not easy to deal with under Kalman model assumptions, it can be approximated by a new Gaussian distribution through the following process which is graphically illustrated in Figure 3.

The original measurement is (x_m, y_m) , and the road section is specified by the end points (x_1, y_1) , (x_2, y_2) , where θ is the orientation of the road with respect to the horizontal axis. The approximation process projects the measurement distribution onto the road and yields the other Gaussian distribution oriented along the road segment and centered at (x_t, y_t) , the projection of (x_m, y_m) on the centerline. σ_l and σ_t are longitudinal and transversal standard deviations of the new distribution, respectively. Hence, the transformed measurement is given by

$$\begin{aligned} x_t &= x_1 + (x_m - x_1) \cos^2 \theta + (y_m - y_1) \cos \theta \sin \theta \\ y_t &= y_1 + (x_m - x_1) \cos \theta \sin \theta + (y_m - y_1) \sin^2 \theta \end{aligned} \quad (8)$$

The covariance matrix, \mathbf{R}_t , is obtained from the original measurement covariance matrix, \mathbf{R} , in the following way:

$$\begin{aligned}
\sigma_l^2 &= \sigma_x^2 \cos^2 \theta + \sigma_y^2 \sin^2 \theta \\
\sigma_{xt}^2 &= \sigma_l^2 \cos^2 \theta + w^2 \sin^2 \theta \\
\sigma_{yt}^2 &= \sigma_l^2 \sin^2 \theta + w^2 \cos^2 \theta \\
\sigma_{xyt} &= (\sigma_l^2 - w^2) \cos \theta \sin \theta
\end{aligned} \tag{9}$$

where $\mathbf{R}_t = \begin{bmatrix} \sigma_{xt}^2 & \sigma_{xyt} \\ \sigma_{xyt} & \sigma_{yt}^2 \end{bmatrix}$ and $\mathbf{R} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{bmatrix}$.

The same comment about the importance of correct location is applicable here. An inaccurate location will result in an incorrect transformation of measurements directly, with degradation even more severe than the dynamic correction. Therefore, the logic to decide when to apply this preprocessing is a key factor affecting the final performance.

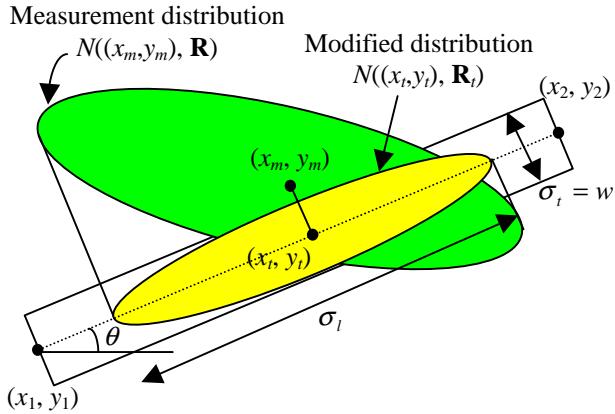


Figure 3: Graphical illustration of the approximated joint distribution of measurement and road segment.

3 HMM-based Tracking Techniques

Other than the Kalman-based trackers described in the last section, we also developed an HMM-based tracker as an extended study of [1] and [6], for making comparisons under the same scenario. Consider a single target moving in a certain geographic area partitioned into a rectangular lattice of cells at discrete time instants, and an HMM tracker λ characterized by the following elements [15].

- The target locations and the sensor observations are modeled by a set of states, $S = \{S_1, S_2, \dots, S_N\}$.
- The set of time-invariant transition probabilities

$$a_{ij} = P[q_k = S_j \mid q_{k-1} = S_i], \quad 1 \leq i, j \leq N \tag{10}$$

where q_k denotes the actual state at time k .

- The observation probability distribution

$$b_i(O_k) = P(O_k \mid q_k = S_i), \quad 1 \leq i \leq N \tag{11}$$

where O_k denotes the observation state at time k .

- The initial state distribution

$$\pi_i = P[q_1 = S_i], \quad 1 \leq i \leq N \tag{12}$$

The Viterbi algorithm is then used to find the best state sequence, $q_1^*, q_2^*, \dots, q_T^*$, given the observation sequence O_1, O_2, \dots, O_T . The highest probability along a single path, which accounts for the first k observations and ends in S_i at time k , is defined as

$$\delta_k(i) = \max_{q_1, q_2, \dots, q_{k-1}} P[q_1 q_2 \dots q_k = S_i, O_1 O_2 \dots O_k | \lambda]. \quad (13)$$

It can be induced that

$$\delta_{k+1}(j) = \max_i [a_{ij} \delta_k(i) \cdot b_j(O_{k+1})] \quad (14)$$

The best state sequence can be retrieved by keeping track of the argument that maximizes (14) for each k and j . The complete procedure can be described as follows:

1) Initialization:

$$\begin{aligned} \delta_1(i) &= \pi_i b_i(O_1), \quad 1 \leq i \leq N \\ \varphi_1(i) &= 0 \end{aligned} \quad (15)$$

2) Recursion:

$$\begin{aligned} \delta_k(j) &= \max_{1 \leq i \leq N} [\delta_{k-1}(i) a_{ij}] b_j(O_k), \quad 2 \leq k \leq T, 1 \leq j \leq N \\ \varphi_k(j) &= \arg \max_{1 \leq i \leq N} [\delta_{k-1}(i) a_{ij}], \quad 2 \leq k \leq T, 1 \leq j \leq N. \end{aligned} \quad (16)$$

3) Termination:

$$q_T^* = \arg \max_{1 \leq i \leq N} [\delta_T(i)]. \quad (17)$$

4) State sequence backtracking:

$$q_k^* = \varphi_{k+1}(q_{k+1}^*), \quad k = T-1, T-2, \dots, 1. \quad (18)$$

There are a number of issues to be addressed. Note that the actual state sequence is usually unavailable and the sensor measurement sequence is thus used instead. The observation probability distribution is a Gaussian likelihood function as mentioned above. The probability transition array, the most important factor in our HMM model, must be location dependent in order to incorporate the ground restrictions. The Viterbi algorithm can be extremely computational and time consuming if the size of the geographic area is large. As a matter of fact, the target can only move onto a reasonable number of spatial adjacent cells, if the cell resolution and the target kinematics are properly chosen. This implies that we can save significant resources by considering a more compact and efficient HMM technically. Since the road network is the only feature in the scenario map, we can assume that the target would like to stay on the road, leaving the non-road cells hard to reach. Here we propose an adaptive HMM tracker where several subscenarios covering the road of interest are defined *a priori*. Each subscenario is associated with a “regional” HMM tracker whose transition array accounts for the covered road segment. The time instants when each regional HMM tracker begins to operate may be determined in advance or based on the estimated target location. Each regional HMM performs the Viterbi algorithm and offers its subtrack. Joining all subtracks at the end forms the entire track. The experimental result in next section demonstrates how this adaptive HMM tracker works geographically.

4 Experimental Results

4.1 Kalman-based Techniques

In this section we present results showing the performance of some alternative Kalman-based ground tracking algorithms. These results were obtained using 50 Monte Carlo runs for each test condition. The scenario is shown in Figure 4, where there are three stationary ground-scanning sensors taking turns to acquire measurements with a regular scanning period of 9 seconds. Each sensor’s characteristic is incorporated into the covariance matrices and likelihood functions for Kalman and HMM approaches, respectively. The scanning period of each sensor can also be made uneven, if one desires so. Therefore, we do not further consider fusing

sensor measurements in one way or another, because a continuous track for the target can be well generated within the limited spatial extent of our scenario. On the other hand, although our transition models are able to predict the target trajectory along the road, non-successive measurements would lead to degradations, especially due to the presence of road junctions. Thus, we assume that there is no large detection loss, e.g., there are not any terrain masking effects that prevent sensors from making detections in certain geographic areas. Sensor performance accuracy depends on the distance to the target, with standard deviation ranging from 50 to 150 meters.

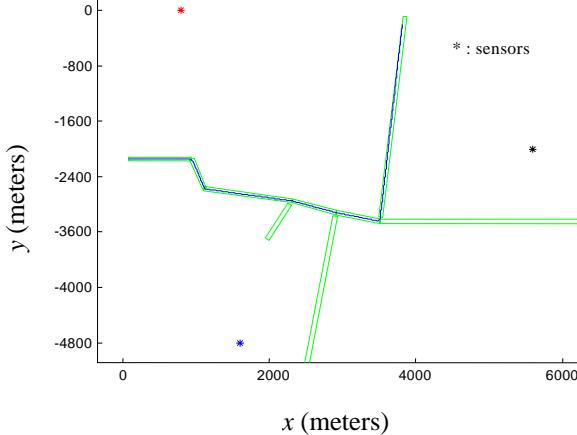


Figure 4: Simulated scenario.

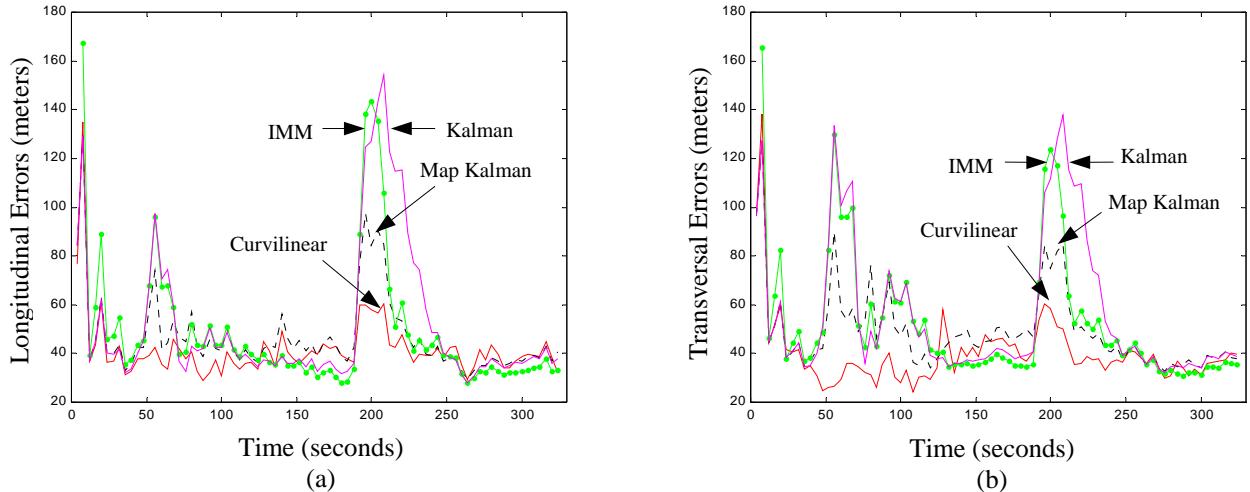


Figure 5: Plots of (a) longitudinal error and (b) transversal error for various trackers.

Assume a ground vehicle is moving along the road where the centerline is depicted, with a constant speed 20 m/s and a transversal acceleration 15 m/s^2 for making turns. There are three road junctions where the algorithms may not be able to identify the correct target heading rapidly.

The performance metrics selected evaluate the accuracy of the estimated location, in terms of the root mean square (rms) of longitudinal and transversal errors. As a benchmark to analyze the advantage of considering ground information, a conventional Kalman filter and an IMM filter with two models have been implemented under the same scenario. Figure 5 plots the errors of four tracking algorithms. Peaks of errors are present at about $t = 180$ s for each algorithm when the sharpest maneuver begins. The IMM tracker performance exhibits a peak of shorter duration than for the Kalman since its adaptation scheme begins just

after the maneuver is detected. However, the IMM does not anticipate the maneuver as the map-based trackers do, since its adaptation scheme is based on the post-maneuver measurement. The curvilinear tracker performs best in all the transversal maneuvers, at $t = 42, 65$, and 186 s. The heading correction allows high smoothness and low bias, reducing the rms longitudinal error 55%~60%, and the transversal 65%~70% with respect to the Kalman filter. The map-tuned Kalman filter reduces rms error at about 40% during maneuvers by increasing the noise to remove the biases. However, when the target reaches the junctions at $t = 126$ and 158 s, the performance of the curvilinear filter is degraded due to wrong heading corrections. Compared to Kalman, its error is about 30% higher. Limiting the corrections, or using additional information such as expected ground movement plans, could reduce this effect when there is a road junction.

In Figure 6, we only compare the map-based techniques. Significant improvement in reducing the transversal errors can be seen due to the preprocessing stage. Again, the errors are raised due to incorrect heading at the junctions and can be restricted in the same way mentioned above.

Finally, to have a more graphical view of what happens with each tracking technique when there is a maneuver, Figure 7 illustrates the estimated target locations (the symbols) and velocities (the lengths of line segments following the symbols) of each tracker in a single run. We can see the map-aided trackers eliminate the biases of Kalman filter successfully, and the curvilinear model is able to maintain a high smoothness and good estimation of velocity at any time.

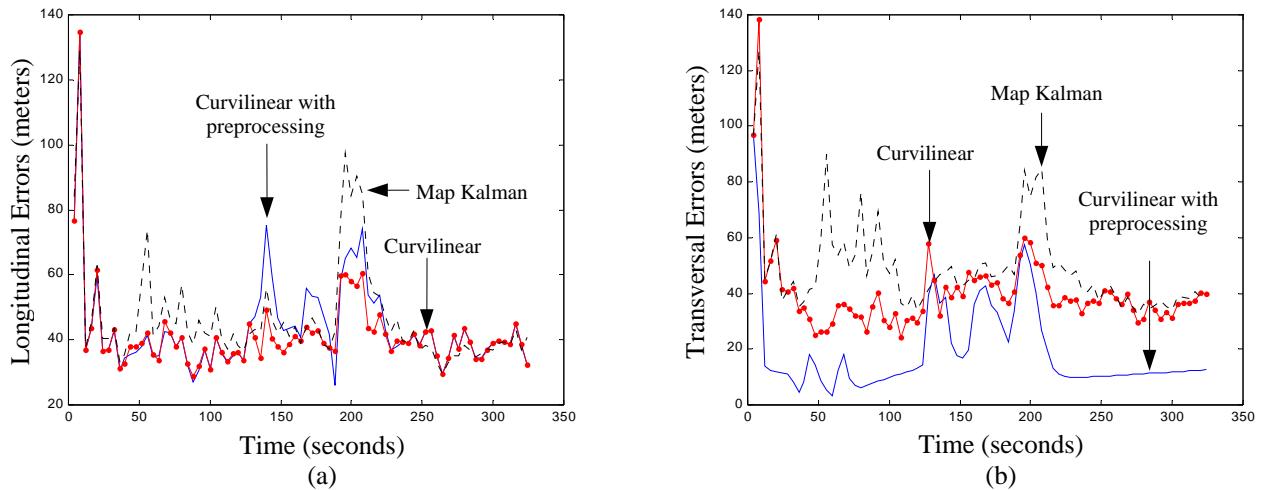


Figure 6: (a) Longitudinal error and (b) transversal error for map tracking algorithms.

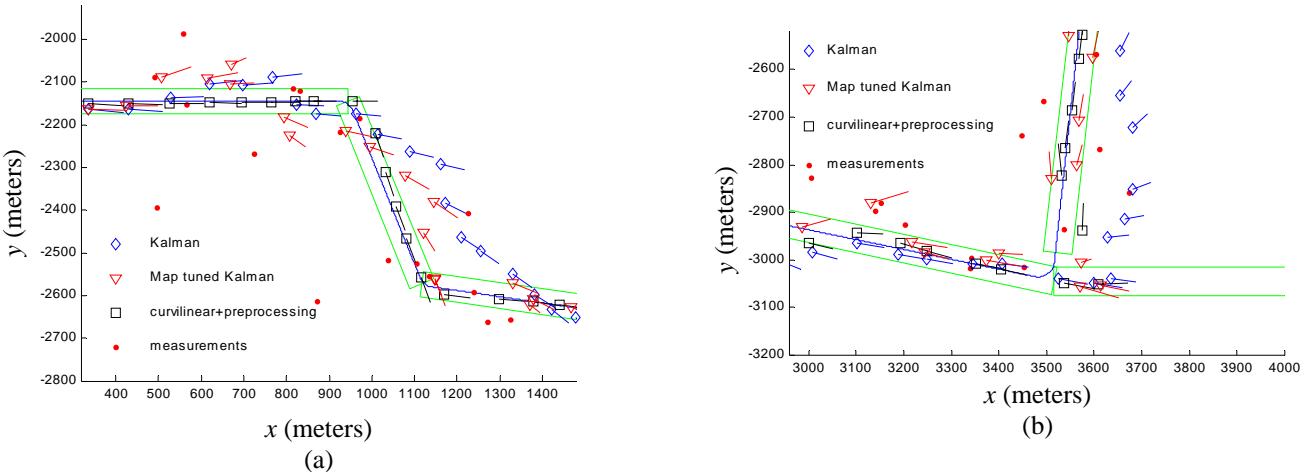


Figure 7: Tracker performance evaluation for (a) the first double turn and (b) the sharp maneuver.

4.2 HMM-based Techniques

For HMM application, the same scenario shown in Figure 4 was discretized into grid cells of resolution 60 m by 60 m. An adaptive HMM tracker composed of 11 subscenarios was built to cover the same road path of interest jointly. As illustrated in Figure 8, each subscenario is a square, containing 11 grid cells in both x and y directions, and the road is one cell wide. Assume that the target may only reach the closest 4 adjacent cells in one single move from the cell it currently resides. The probability transition array can thus be determined in the following way. If the target is off the road, it intends to reach a nearest road cell, whereas if it is on the road, it will move onto all immediate adjacent road cells with equal likelihood at next time instant. For the first regional HMM, the initial state is given by the sensor measurement; for others, it follows the last estimated state of the previous regional HMM. The initial state probability distribution is then completely committed to the selected initial state.

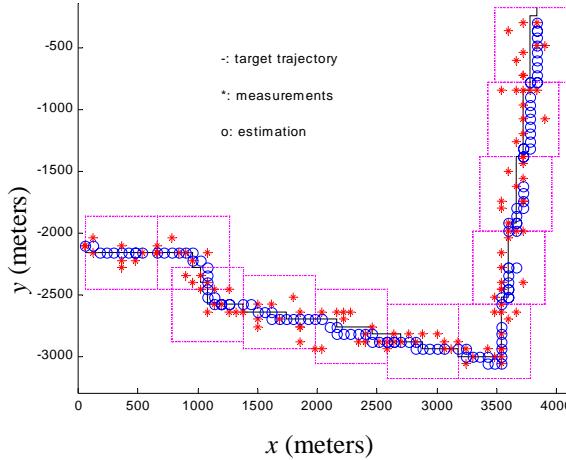


Figure 8: Adaptive HMM Tracker performance evaluation.

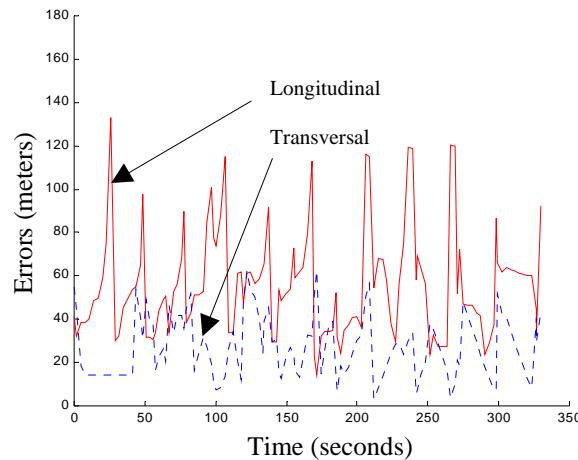


Figure 9: Longitudinal error and transversal error for the adaptive HMM tracker.

Figure 8 shows the estimated target locations of the adaptive HMM tracker for a single run in the discrete spatial domain. Visually, we can see that the track stays close to the trajectory, at most one cell away, even at

the sharpest maneuver. This implies a small transversal error. However, the longitudinal error is much greater. It can be explained as follows. Due to the feature that Markov models are memoryless, the transition array is built in such a way that the target does not remember where it had been in the past. When the target is on the road, there are at least two possible reachable road cells, forward and backward along the path, at next moment. If it moves backward, the track lags behind the trajectory by two cells. As this effect for potential duplicate estimates propagates spatially, the track provided by each regional HMM is usually shorter than expected. This increasing longitudinal lag is corrected as soon as the next regional HMM becomes dominant, whose initial state can be chosen as the closest cell from the last estimation. Figure 9 depicts the results for 50 Monte Carlo runs. It can be seen that the peaks of longitudinal error are present at the time that each regional HMM tracker ends. The transversal error is generally much smaller and is not obviously related to edges of subscenarios. Compared to the Kalman techniques, the adaptive HMM tracker yields larger longitudinal but smaller transversal errors; both are independent of target maneuvers.

5 Conclusions

We have developed and evaluated several tracking techniques in two categories, Kalman-based and HMM based approaches, for a single target moving on a road-based geographic terrain. When the ground information is unavailable, the conventional Kalman filter and IMM with two models have roughly the same performance in terms of estimation errors. To reduce the peaks of errors due to transversal maneuvers, we have implemented three methods to take road structures into account properly. The first is to tune the variance of the process noise for maneuvers. The second is the curvilinear model that considers the road orientation in target dynamics, but may become unstable if the target heading changes substantially in a short time. Both methods can be improved by an additional stage to preprocess the sensor measurements.

An adaptive HMM tracker has also been proposed in order to save computation time for the Viterbi algorithm due to the large size of the scenario. A number of HMM subscenarios are predetermined to cover the road path of interest jointly. These regional HMMs take turns to operate and keep the transversal errors small. Due to the road-based transition array, some regional HMM may lose tracks at the end, resulting in large longitudinal errors. The adaptive HMM tracker is not sensitive to transversal maneuvers.

Generally speaking, the HMM-based tracker is more time consuming than Kalman-based trackers. However, it can freely incorporate any terrain features, target kinematics, and even military doctrines into the transition array such that the track can be more accurate. Kalman-based trackers are efficient and robust, whose performance can also be improved by incorporating road structures. Future studies should investigate how these approaches may be refined technically if more topographic information is available.

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